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Research Article

An EMG-based Prosthetic Hand Design and Control Through Dynamic Time Warping

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Abstract – This study presents a new method to control prosthetic hands by utilizing Dynamic Time Warping (DTW) to accurately evaluate muscle contraction similarity. The objective of this research is to offer precise grip control for individuals who require prosthetic solutions. The study focuses on whether the implementation of the DTW algorithm can significantly improve the control accuracy and usability of myoelectric prosthetic hands. The initial prototypes of the prosthetic hand demonstrated promising results in achieving fundamental gripping functions through DTW-based control. The proposed prosthetic hand design points to the importance of leveraging advanced control algorithms, such as DTW, to address the specific needs of individuals requiring prosthetic solutions. By improving the prosthetic technology, the study aims to provide solutions that meet the unique challenges faced by individuals who are in need of a prosthetic hand.

Keywords – Biomechatronics, Myoelectric Signals, Prosthetic Hand, Feedback Control.

I. INTRODUCTION

Prosthetic limbs have been ongoing research since the 15th century B.C. in Egypt [1]. Which was used mostly for cosmetic purposes. Later on, more functionality was added to them with the use of metal parts to be pulled to grab objects, lock, and bend [1]. Currently, prosthetics are more advanced all the way up to being used by Electromyography (EMG) signals, which are the biological signals generated by the muscle contractions [2]. The development of prosthetic technologies, particularly more simplistic and feedback-oriented myoelectric-controlled prosthetic hands, is a significant step towards improving the quality of life for those who have lost their hands. In the wake of natural disasters like earthquakes, where limb injuries are common, the need for advanced prosthetic solutions becomes even more urgent.

According to Uluöz et al. [3], during the earthquake in Kahramanmaraş (2023) a total of 560 patients were hospitalized in a single orthopedic clinic where 31 of the patients underwent amputation. Similarly, in the same earthquake, Ergani et al. [4] provide statistics from a single plastic surgery department, where a total of 120 patients upper extremity soft tissue injury was seen in 46.2% of the patients, and amputation was performed in four patients, three of which were in the upper extremity and one in the lower extremity. Another article Ziegler-Graham et al. [5], provides data that one in 190 Americans is currently living with the loss of a limb and estimates that if it is unchecked, this number may double by the year 2050.

Even when the myoelectric prosthetics were correctly applied, according to Franzke et al. [6], physical therapists and myoelectric hand users, complain about how the myoelectric signals can’t be controlled consistently and how actions feel rough, leading to dissatisfaction reported by users of myoelectric hand prostheses, which has led to rejection rates of the myoelectric prosthesis as high as 23%. Many studies [2-5] attempt to solve this problem with different approaches. Atasoy et al. [7] propose a 24 Degrees of Freedom (DoF) prosthetic hand with successfully classified Electromyography (EMG) data, taking advantage of the complex mechanical design to successfully provide various grips. Wattanasiri et al. [8] focus on the lack of grip patterns on prosthetic hands with a unique multifunctional grip mechanism using a single actuator. Ahmed et al. [9] provide a different perspective using pressure sensors instead of myoelectric sensors for muscular signals, however, as mentioned in their article, their design was not meant for high torque situations. Ismail et al. [10] follow a practical approach and provide a user interface (UI) to record data from the muscles on a five-fingered prosthetic hand.

This study represents a simpler multidisciplinary approach, drawing from engineering, biomechanics, and rehabilitation sciences, to develop a myoelectric-controlled prosthetic hand with a focus on earthquake rehabilitation. In essence, this study seeks to contribute to the physical and mental health of individuals affected by limb loss. Beyond immediate victim aid, this study has the potential to help the self-reliance of the local economy. The ability to produce prosthetic hands locally not only addresses the immediate needs of earthquake victims but also reduces dependency on imports, thereby improving the local economy by promoting sustainable development.

II. MATERIAL AND METHOD

The workflow of this study was separated into multiple parts as shown in Figure 1 below, creating an outline of the process of this study.

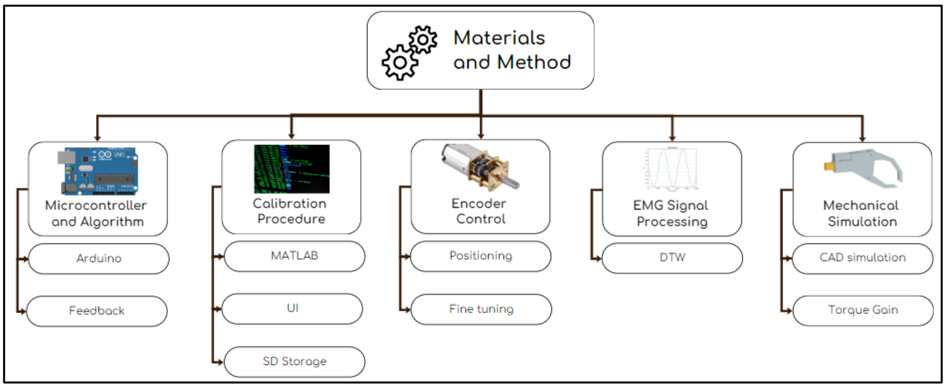

Figure 1. Workflow of the study

Choosing a central control unit, in this case, and Arduino, which will combine the rest of the elements of the prototype. A calibration focusing on the user is another important step, due to how each person's muscles send different signals, the system has to be adaptive to every person and stay the same for extended periods. Therefore, a MATLAB UI and an SD card were used to fill this requirement. Users will be able to calibrate using a simple UI and the calibration values will stay in the SD card. The hand movement to grab objects had to be precise so the prosthetic hand's grip was more controlled. To gain precise control of the DC motor was done with an Encoder. Which measures rotations of the DC motor, making more precise control possible. As the prosthetic hand is controlled mainly with an EMG sensor, it requires an algorithm to differentiate the difference between a proper and improper signal. This was done inside the Arduino using a control algorithm called Dynamic Time Warping (DTW). DTW compares two shifted timelines and generates a similarity value like in Figure 4 and Table 1. This similarity helps Arduino to understand if the signal was the one that was recorded or not. Simulations later on had to be done in order to ensure the DC motor could provide proper torque from the mechanical advantage of the worm gear inside. This was done with the help of a simulation program called Siemens NX.

Below in Figure 2, is a simplified model that shows the mechanical system of the prosthetic hand. The hand's motion begins with a DC motor located at the center of the mechanism. The motor applies rotational force to a worm gear that is connected to its shaft. This worm gear is a crucial component that converts the rotational motion into linear motion through a slider joint arrangement.

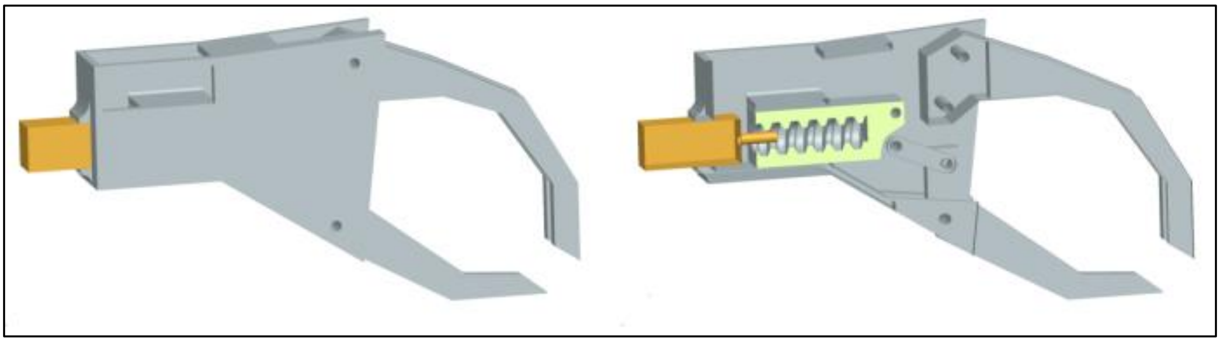

Figure 2. 3D Model of the Prototype on the left with the cross-section for internal view on the right

The slider joint generates linear motion that moves along a rail system. As the slider joint moves along the rail, it transfers force onto two levers, each serving as a mechanical linkage to the fingers of the prosthetic hand. These levers help the rotation of the fingers around a pin joint, which enables the hand to open or close in response to user input. This mechanism ensures a robust gripping action. One of the significant advantages of this mechanical arrangement is the utilization of the worm gear for linear motion conversion. This configuration provides a significant mechanical advantage, allowing the source DC motor to be compact in size and torque while still providing sufficient force to operate the prosthetic hand effectively. Additionally, the worm gear mechanism offers inherent holding torque, effectively resisting external forces that may attempt to force the hand open against the user's intended grip.

The EMG data will be acquired by the EMG probes attached to a person's muscle as illustrated in Figure 3 below. The gathered data gets filtered and sent into Arduino for further processing. As illustrated, EMGs usually have three probes to gather data. One of them is live, which generates the signals, neutral, which is the reference point for the live probe, and finally, the ground probe, which is the filtering probe.

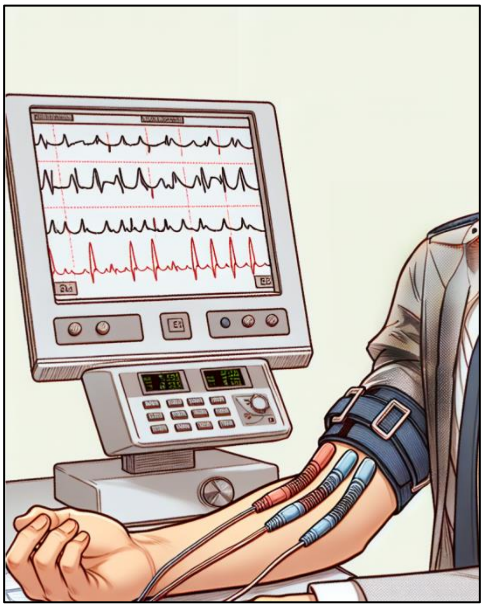

Figure 3. AI generated illustration of EMG probes and data analysis.

In Figure 4 below real EMG data is shown, the signal fluctuation corresponds to muscle contractions which were filtered through the DTW algorithm. Which gets filtered and put through DTW for use. Each pulse is an activity read from the muscle.

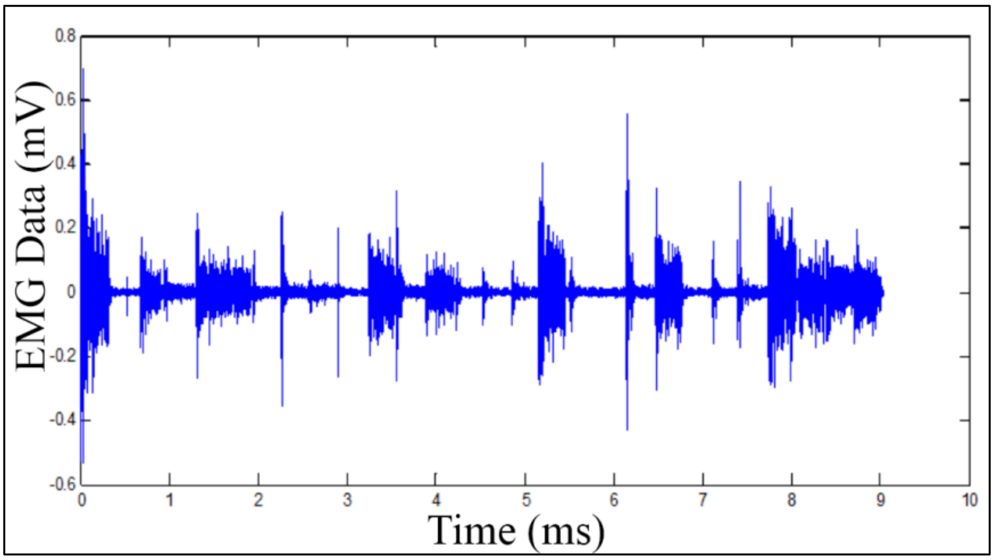

Figure 4. Example of an unfiltered EMG data. Adapted From [11]

This data later be filtered by the EMG SpeedStudio which has a build in filtering system. Filtering system gets rid of the electrical noise such as the nearby equipment and biological noise, creating a more reliable data for further processing.

Table 1. Example DTW Matrix which uses the data from Figure 5.

9	1.52	∞	2.31	3.09	2.11	2.2	2.29	2.28	2.3	2.28
8	1.57	∞	2.26	2.6	1.89	2.15	2.24	2.25	2.25	2.27
7	0.93	∞	2.26	1.72	2.29	3.06	2.84	2.64	2.65	2.68
6	1.06	∞	1.62	1.48	2.16	2.45	2.11	2.01	2.06	2.09
5	1.52	∞	1.11	1.89	1.77	1.68	1.51	1.55	1.6	1.63
4	2	∞	1.06	1.94	1.55	1.37	1.54	1.89	2.07	2.26
3	1.91	∞	0.63	1.51	1.29	1.2	1.45	1.64	1.81	2
2	1.74	∞	0.29	1.17	1.12	1.21	1.29	1.47	1.64	1.78
1	1.69	∞	0.12	1.12	1.17	1.31	1.34	1.47	1.59	1.73
0	1.71	0	∞	∞	∞	∞	∞	∞	∞	∞
j		1.56	1.57	0.69	1.74	1.83	1.66	1.56	1.57	1.55
	i	0	1	2	3	4	5	6	7	8

Abdhul et al. [2] explain how complex EMG signals can be which need to be filtered and amplified to be more consistent and reliable. After the filtering, EMG signals go through an algorithm called Dynamic Time Warping (DTW). In Figure 5 an EMG example data is shown, the signal fluctuation corresponds to muscle contractions which were filtered through the DTW algorithm. In [12] DTW model is explained to be an algorithm used to measure the similarity between two sequences of data points. It is commonly used in time series analysis when traditional distance metrics like Euclidean distance are inadequate due to timelines being shifted back or forth. Misalignment or variability in the timing of events creates an inaccurate model, DTW prevents this problem. In this study, The DTW algorithm was used to assess muscle contraction similarity. The DTW algorithm compared the resting and contracted muscle signals, generating a similarity value. This methodology ensures responsive and naturalistic prosthetic hand operation, closely mirroring the user's intended actions.

In Figure 5 on the left side, there are two similar signals, however, they are slightly different and the time intervals are at different sizes. DTW generates a similarity value using the algorithm on the right side of Figure 5. This algorithm generates the data in Table 1. For example, as in Equation (1) below, the initial value d(xi,yj) is the absolute value of the subtraction of the distances between the first and second data points in the same time interval. The next part is the minimum of the bottom, left, and bottom left numbers in the DTW matrix in Table 1. Assembling the DTW matrix the top right-most cell provides a similarity value in Table 1, this value is 2.67. The further away the value is from 0, the less similar the data lines are. This algorithm was performed instantaneously in Arduino to measure the similarity constantly to catch a similar incoming signal to the calibrated values.

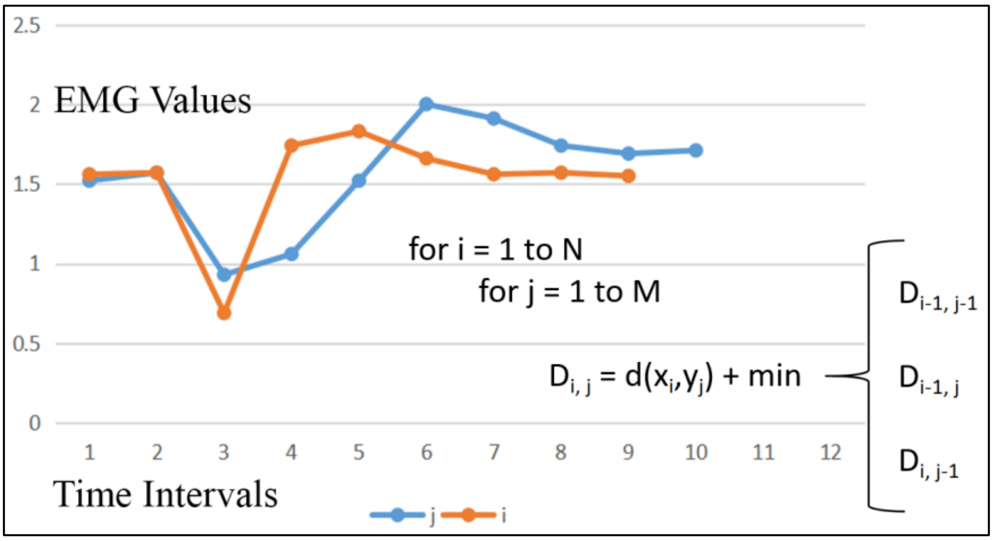

Figure 5. Example DTW values and formula.

$$D_{1,2} = |1.69 - 1.57| + min \begin{cases} D_{0,1} = \infty \\ D_{0,2} = \infty \\ D_{1,1} = 0.12 \end{cases} = 0.29 \qquad (1)$$

The data collected from the DTW similarity matrix was generated with the help of a user interface. Hoshigawa et al. [13], discussed how myoelectric prosthetic hand control is limited even with machine learning algorithms. However, in this study, another control approach was taken with a user interface (UI) based calibration method, including a more consistent algorithm.

In Figure 6 below, the bottom left graph gives information on how far the simulated slider is being pushed by the DC motor and the worm gear, the linear graph tells us that the velocity is 2.5 mm/s constantly. The top right graph provides valuable information about the right finger. The bottom right graph provides important information about the right finger.

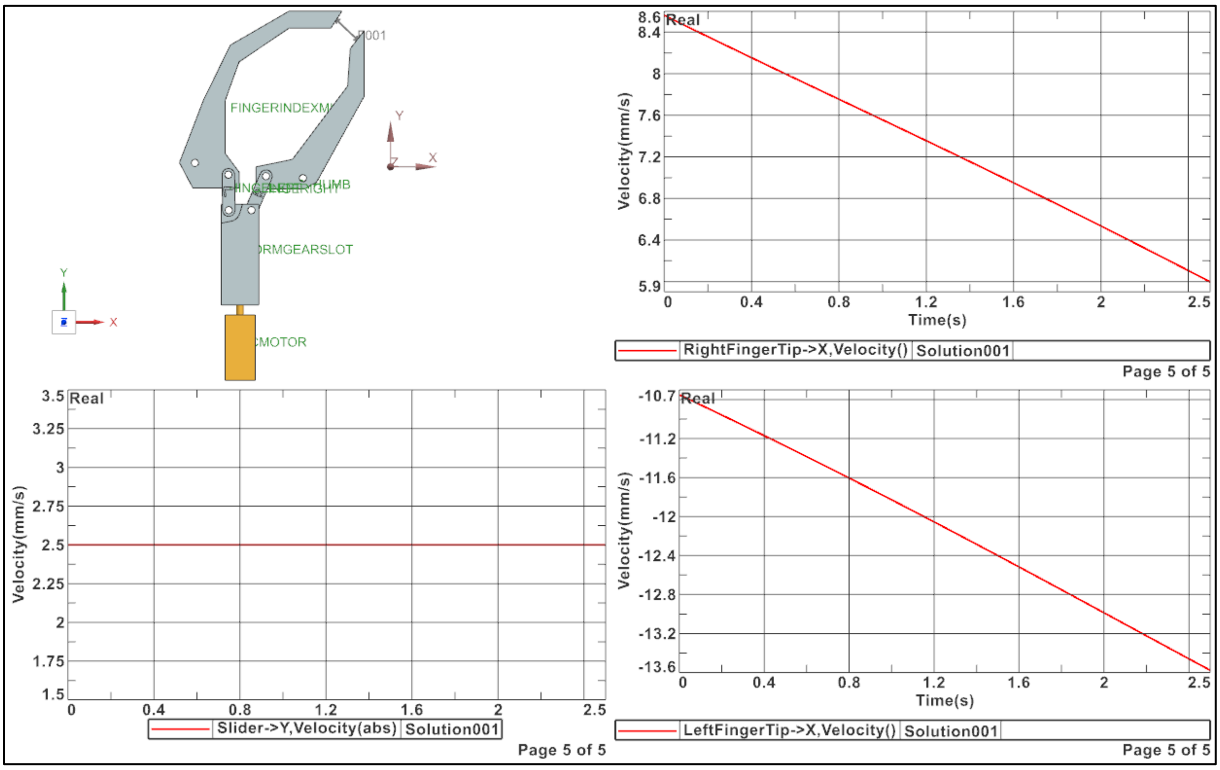

Figure 6. Kinematic model simulations data

Figure 7 below provides a kinematic diagram and the calculations below a kinematic model. Using these models the prosthetic hands control can be further optimized by more precisely controlling the gripping speed.

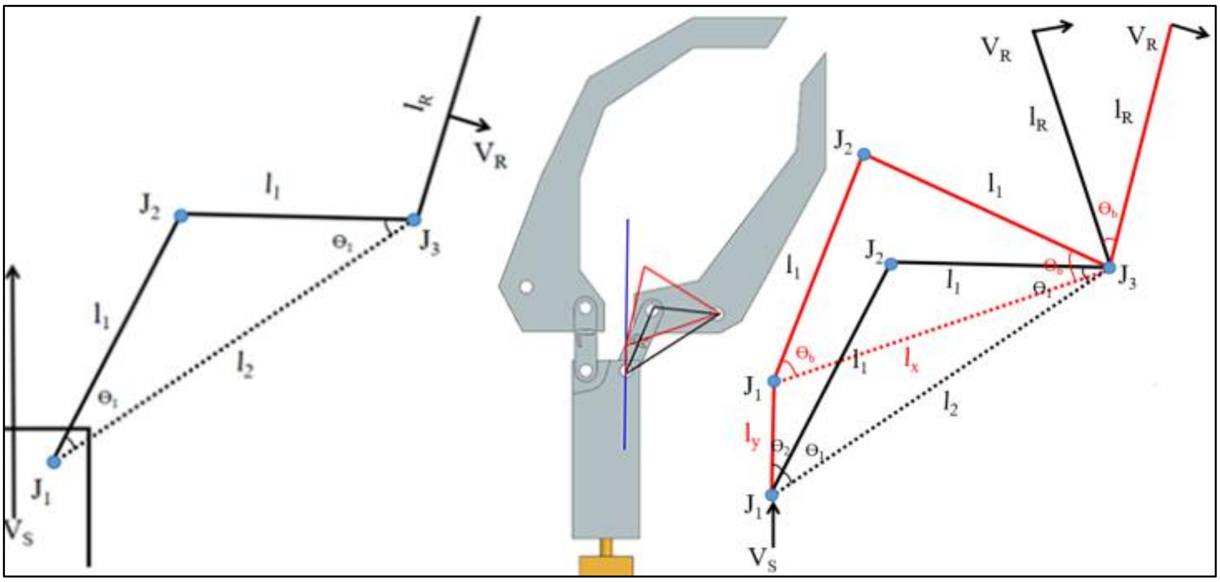

Figure 7. The kinematic diagram above marks the distances, angles, and rotation points for the kinematic model.

Using the kinematic diagram above in Figure 7, the kinematic equations below can be driven. Which can be used to further optimize the processed data from various sensors like encoder and EMG. Creating a more precise control of the prosthetic hand.

$$l_y = V_s \cdot t \quad \& \quad l_x = \sqrt{l_y^2 + l_2^2 - 2 \cdot l_y \cdot l_2 \cdot \cos(\theta_1 + \theta_2)} \tag{2}$$

In Equation 1 above the changes in distance for any given time are donated and tied to time variable “t”.

$$l_1^2 = l_1^2 + l_x^2 - 2 \cdot l_1 \cdot l_x \cdot \cos(\theta_b) \rightarrow \cos(\theta_b) = \frac{l_x}{2 \cdot l_1} \rightarrow \cos^{-1}\frac{l_x}{2 \cdot l_1} = \theta_b \tag{3}$$

Later using the law of cosines, the change in angle for the given time “t” is found.

$$\omega = \frac{d\theta_b}{dt} \quad \& \quad V_R = \omega \cdot l_R \quad \& \quad V_1 = \omega \cdot l_1 \quad \& \quad V_s = \pi \cdot Pitch \cdot RPM \tag{4}$$

Lastly converting the rotational speed (RPM) of the motor over the wormgear into linear velocity, all the previous equations can be tied together.

$$V_R = \omega \cdot l_R = \frac{d\left[\cos^{-1}\frac{l_x}{2 \cdot l_1}\right]}{dt} \cdot l_R = \frac{d\left[\cos^{-1}\frac{\sqrt{l_y^2 + l_2^2 - 2 \cdot l_y \cdot l_2 \cdot \cos(\theta_1 + \theta_2)}}{2 \cdot l_1}\right]}{dt} \cdot l_R \tag{5}$$

$$V_R = \frac{d\left[\cos^{-1}\frac{\sqrt{(V_s \cdot t)^2 + l_2^2 - 2 \cdot (V_s \cdot t) \cdot l_2 \cdot \cos(\theta_1 + \theta_2)}}{2 \cdot l_1}\right]}{dt} \cdot l_R \tag{6}$$

Combined equations 2,3 and 4 results in the velocity at the tip of the fingers at any given time “t”.

III. RESULTS

The data below in Figure 8 is generated by Siemens NX while the fingers open and close twice under 85 Newtons of force. Which means gripping and manipulating an object around 8.5 kg. The torque is between 270 Nmm and 290 Nmm between ungripping and gripping events.

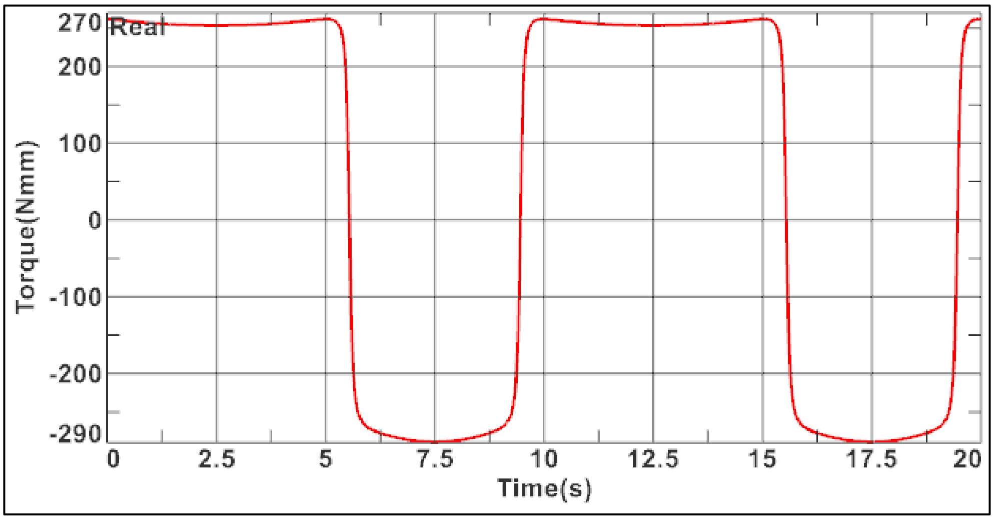

Figure 8. Simulation result of the required torque at all angles, two different directions.

This data provides valuable insights into the mechanical performance of the prosthetic hand. This force is facilitated by the mechanical advantage of the worm gears and translates to an approximate grip force of 85N or 8.5kg. This level of force is practical and achievable for most available DC motors with simple reductors. The torque requirement is well within the capabilities of readily accessible motor systems, proving the feasibility and scalability of the prosthetic hand's design.

Below in Figure 9, there are three simulated EMG data points. The Dynamic Time Warping (DTW) algorithm was used to differentiate between muscle signals and provide precise control. The DTW algorithm was applied to a simulated dataset that comprised signals from different muscle contractions, denoted as "i," "j," and "k." By comparing the similarity values of datasets "i" and "k" to a reference signal "j," it was observed that the "i" dataset showed a similarity value of 2.33, whereas the "k" dataset showed a value of 1.2. This confirms that the "i" dataset is less similar to the average value line than "k", demonstrating the effectiveness of DTW in discerning between different muscle activation patterns. This shows the usefulness of DTW as a viable method for analyzing EMG signals and enabling precise control of prosthetic hand movements.

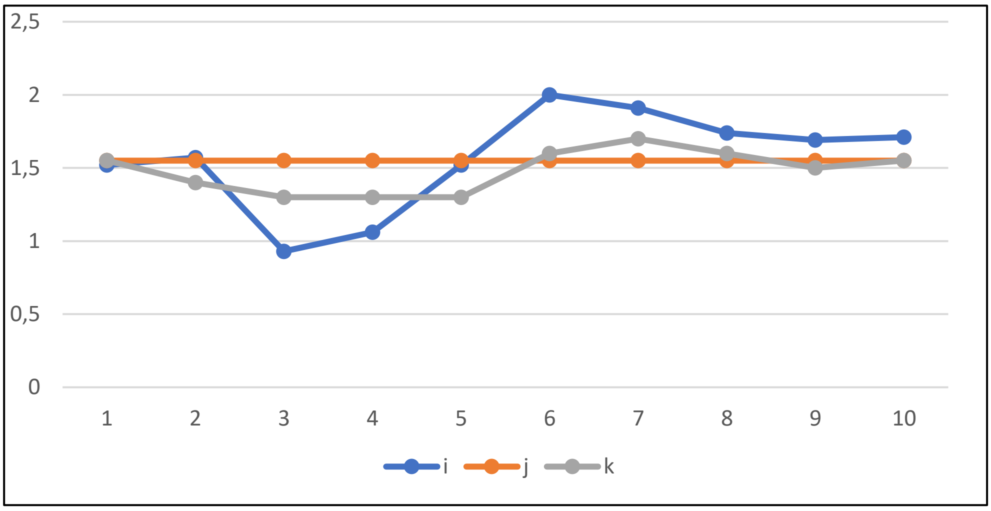

Figure 9. Three simulated EMG signal examples “i”, “j” and “k”.

By presenting these results, the study highlights the practical feasibility and effectiveness of both the mechanical design and control algorithms in the prosthetic hand.

IV. DISCUSSION

The prosthetic hand in the study is prepared considering the feedback from the existing prosthetic hand users [6]. The study provides a different approach for the control algorithms and mechanical design. In a review article Chen et al. [14], discuss how most prosthetic hands are controlled by non-negative matrix factorization (NMF) and deep learning algorithms. However these algorithms are focused on as mentioned by Chen et al. rely heavily on tedious machine features and fail to meet the requirements of current human–machine interaction scenarios, one example is real-time responsiveness. The control algorithm in this study takes advantage of a DTW algorithm to provide a reliable response to user inputs. Most prosthetic hand mechanisms focus on cost-effectiveness, however, the mechanism in this study focuses on creating a more reliable and precise grip with high torque. Open Bionics [15] for example focuses on a cost-effective simple custom-made 3D printed design, which has high adaptability but lacks mass production properties.

The prosthetic hand was able to provide a consistent response, however, there are still problems and limitations to improve on. The control algorithms are not perfect, there is always room for improvement and optimization, with future tests, the algorithms will keep improving and provide more accurate and precise control. In prototypes the battery life wasn’t a big issue, however, in the future this could require stronger and more expensive alternatives, changing the cost-effectiveness of the prototype accordingly. Material selection for the final product is considered to be titanium as it is a fairly common, light, and strong material. However, it is hard to manufacture, and therefore, costly, perhaps in the future, there can be a cheaper alternative. Currently, the calibration is made by a computer-based UI, which requires the prosthetic hand to be connected to a computer. However, in the future, the whole calibration process can be done with the prosthetic hand itself without a dependence on external equipment. The central controller Arduino has a limited capacity of code it can run, eventually as the algorithms get more sophisticated, a more powerful controller might need to be swapped in with it.

V. CONCLUSION

This study explores the development of a prosthetic hand that can be controlled by muscle signals. The hand includes sensors and advanced algorithms like DTW to process the signals. Through testing and optimizations, it has progressed in achieving functional capabilities. The use of locally available materials and production processes to create a sustainable and cost-effective solution can be particularly useful in regions that are prone to natural disasters like earthquakes. The prosthetic hand includes an EMG sensor and an optimized DTW algorithm, to make it more responsive and user-friendly, catering to the diverse complaints and needs of users with limb loss. The computer simulations and mechanical calculations optimized the consistency of the prosthetic hand's functionality. This study represents a step forward in the development of practical and accessible prosthetic solutions, which have the potential to improve the lives of individuals in need, especially in Turkey where earthquakes are a very relevant problem.

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